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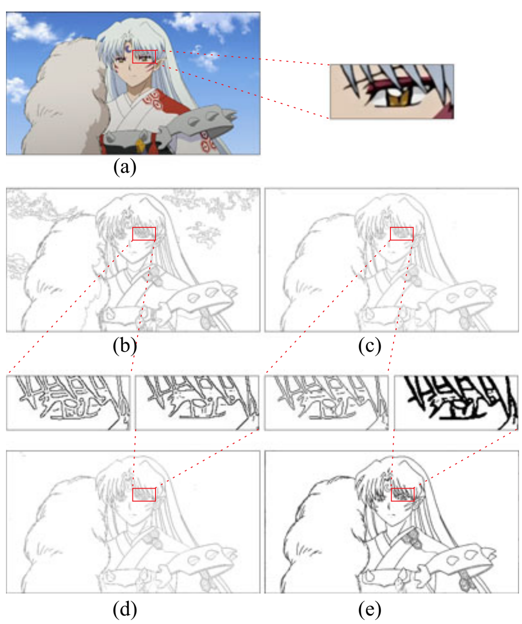

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A Dynamic Mode Decomposition Based Edge Detection Method for Art Images

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Abstract: Edge detection is a widely used feature extraction method in various fields, such as image processing, computer vision, machine vision, and so forth. However, it is still a challenging task to extract edges from art images, due to the false edge, shadow, and double lines of art images. In this paper, we propose a dynamic mode decomposition algorithm (DMD) based method for edge detection of art images. This is achieved by proposing a new color space based denoise method to deal with the shadow issue. Then, the false edge and double lines can be resolved by employing DMD method, which can be used to extract sparse features from the denoised images. Here, the sparse features have been enhanced by a new designed eight direction gradient operator. Finally, the effectiveness of our method will be demonstrated through detecting the edges of three classical types of art images (Comic, Oil Painting, and Printmaking).

Index Terms: Image processing, image edge detection, filtering, optical filters, optical engineering.

1. Introduction

Edge detection is a widely used feature extraction method in image processing [1], [2], computer vision [3], [4], and machine vision [5]–[7]. This is because the edge is the most important element of an image. For example, in art creation and art appreciation, edge is the concrete expression of artists' inspiration. Currently, most researches focus on edge detection for natural images, such as Sobel operators [8], Kirsch operators [9], Prewitt operators [10], [11], Roberts operators [12], Laplacian operators, and so on. The main idea of these methods is using differential operator to calculate a first-order derivative expression. Basically, these algorithms have good performance for natural images. However, these methods cannot directly be applied to art images, due to the following reasons:

1) False Edge: the extracted edge, which is actually not an edge. The extracted cloud in Fig. 1 is such an example, it should not be extracted, because the cloud is just the background of the comic.
2) Shadow: the horn button in the cloth of Fig. 1 should not be extracted.

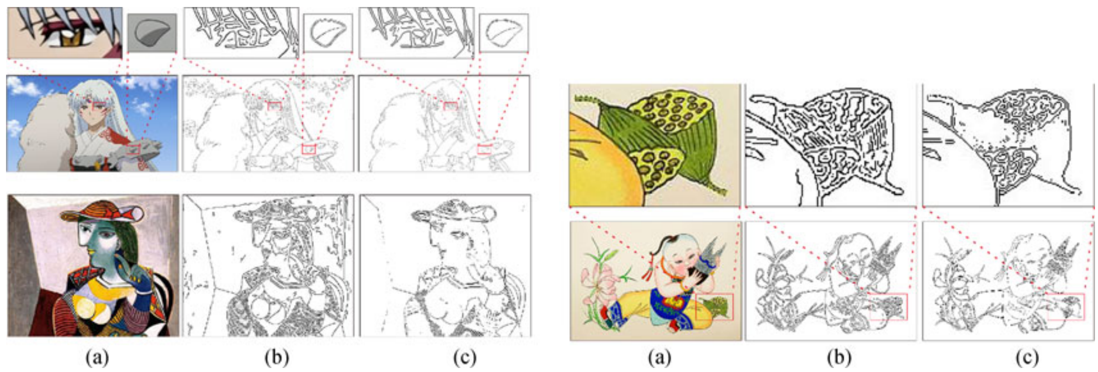

Fig. 1. The existing edge detection algorithms detect the results in comics, oil paintings and printmakings. (a) The original art images including comic, oil painting and printmakings. (b) The results obtained by Canny edge detection. (c) The results obtained by Sobel operators. The pictures are from: "InuYasha" (left-top), "Pablo Picasso's oil painting" (left-down), and "http://www.sohu.com/a/123599892_554521" (right), respectively.

3) Double Line: a dense line will be extracted into two edges by existing differential operator methods. The extracted eyes in Fig. 1 are such an example. The results are lack of a clear outline.

Art images contain Comic, Oil Painting and Printmaking, which have different features:

1) Comics: in order to show different artistic effects, comics usually contain rich colors and Shadows. These features are easily judged as edges by existing methods, as shown in Fig. 1.
2) Oil paintings: in order to express the author's feelings, oil paintings usually contain very complicated and no uniform lines in Fig. 1. Due to the uneven thickness of these edges, existing methods cannot be detected well. There are many False Edges in the result.
3) Printmakings: printmakings are often filled with dense lines to foil the theme style. These dense lines lead to the Double Line problem, as shown in Fig. 1.

Therefore, in this paper, we propose a dynamic mode decomposition (DMD) [13] based edge detection algorithm for art images. The main idea of our algorithm contains three steps: Firstly, in order to resolve the shadow issue, we propose a color space denoise method. This is achieved through using the maximum brightness difference. Secondly, a sparse feature enhancement filter called EDGO (Eight Direction Gradient Operator) is designed as the preprocess for the DMD based edge detection algorithm. Finally, DMD algorithm is a very effective method to analyze data set, which has been used in fluid mechanics. DMD algorithm is employed to extract the sparse edge from the denoised art images. It can separate the original data set into a low rank matrix and a set of sparse matrices, and art images have strong sparseness as well.

The remainder of this paper is organized as follows: Section 2 provides a brief survey on related work. In Section 3, we describe our main idea. Color space based denoise method is detailed in Section 4, and then for our sparse feature enhancement filter EDGO in Section 5, followed by the DMD method for edge detection in Section 6. The effectiveness of the proposed approach is presented through the comparison with existing schemes in Section 7. Finally, we conclude this paper and discuss several possible future work in Section 8.

2. Related Work

In this section, we will introduce three kinds of edge detection algorithms including the traditional edge detection algorithms, edge detection algorithms based on Gaussian function and other methods.

2.1 Existing Edge Detection Algorithms

There are some universal edge detection algorithms [14]–[17] such as Krisch operator, Roberts operator, Sobel operator, Prewitt operator, Laplace operator and so on. The main step of the differential operator algorithms is to calculate a first-order derivative expression such as the gradient magnitude, and then searching for local directional maximum of the gradient magnitude. For example, the Roberts operator computes the sum of the squares of the differences between diagonally adjacent pixels to get high precision of the edge [18]. However, it is easy to lose some information about the edges, resulting in discontinuous and unsmooth edges. Another point is that it is difficult to suppress the noise. Although Sobel operator and Prewitt operator are more accurate and complete, the result from the two operator algorithms may have the false edges. The main problem is that, if we want to maintain the continuity and smoothness, they cannot make it [19]–[22].

Aiming at the problems of the operators above, many papers have done various improvements [23]–[28]. The main method to develop the performance of the universal operator algorithms is to reduce noise using filters. Canny operator [29] has improved the ability to suppress noise and smooth the edges with Gaussian filter [23], [24]. It finds the intensity gradients of the image, applies non-maximum suppression to get rid of spurious response to edge detection and uses the double thresholds to determine edges. Canny operator can balance the noise suppression and edge detection and it has a good performance for the edge detection. However, to reduce noise with some filter will make the image blurred. Furthermore, Canny operator cannot keep good results in the multi-scale space. That means if we change the scale of the images, the edges of its result will not maintain good continuity and smoothness. Finally, the result will not be vivid from an artistic point of view.

Recently, with the development of fuzzy mathematics [30]–[32], neural net [33], [34] and machine learning [35]–[39], people have been exploring and applying them to image edge detection. The most representative algorithm is the edge detection based on fuzzy sets proposed by Pal and King [40]. Using the neural net to extract image edges has become a new branch of research. Using the fuzzy theory for edge detection [41], we first need to regard an image as a fuzzy set. Then, the image is mapped to a fuzzy feature matrix. The process of fuzzy enhancement [42] is to reduce the ambiguity of the image. After the fuzzy enhancement, the extracted edge information is more meticulously. These methods are simple in calculation and good at processing results, but slow in speed and poor in stability. Additionally, there are some edge detection algorithms based on Fractal Theory [43]. The main idea of these methods is to calculate the fractal feature map of the image based on the specific fractal model. After that, using the fractal feature map to get the target area or edge by some strategies. These methods will not perform well with images, which have complex background. It is not obvious for the contrast between the target and the background in the fractal feature map. It will reduce the effect of edge detection. These techniques will only show better results relatively and will not have good results for non-natural images.

2.2 Dynamic Mode Decomposition

Sun *et al.*'s work also used the flexibility of temporal-spatial information to construct a method for image retrieval based on time and space [44]. Zhao *et al.* based on the dynamic super-resolution imaging method to improve the signal-noise-ratio (SNR) to obtain high resolution (HR) images [45]. Huang *et al.* reduced image noise by studying image sensors [46]. The reason we use the DMD method is that the DMD has the characteristics of extracting the sparse structure from the time serial data. We will introduce the development of this method. DMD method has been widely used in fluid mechanics [47]. Most fluid analysis uses the DMD method for low rank data reconstruction. DMD is an algorithm for short-term evaluation of nonlinear power systems. It is able to process experimental data and simulation data. DMD is used to analyze disease transmission as well. Using DMD to reduce the high dimensional data, can be found in the disease detection data from the sparse measurement to deal with the challenges of disease monitoring. In the computer field, the DMD method can be used to process some big data as well and it has shown the more excellent ability than many other algorithms. One successful instance is that applying DMD method to separate the foreground and background of the video. The foreground of video is considered to be a sparse matrix, by which DMD can extract the sparse part of temporal data. Thus, it can be

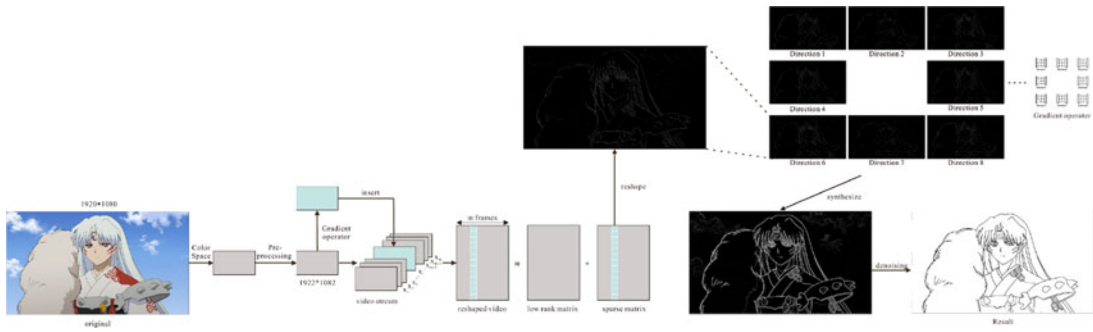

Fig. 2. An edge detection framework for art images. This framework is divided into three processes. First of all, preprocessing art images and using color space to noise reduction. Secondly, using the EDGO to enhance the sparse features. Finally, using the DMD method to get the result of sparse edge.

used to separate foreground and background [48], [49]. In this paper, we use DMD to extract sparse borders of art images.

3. Our Idea

We provide an edge detection framework for art images to solve the problems including false edge, shadow and double lines. In the art image, the false edge is no need to be extracted. Because of the painting skills, false edges often appear in oil paintings. In comics, in order to show different artistic effects, comics usually contain rich colors, shadows. The shadows will interfere with edge extraction. It often appears double line by using the existing algorithms for extracting the edge of printmakings. The double line is easy to cause ambiguity. These problems cannot be solved by the existing edge detection algorithms. Therefore, we used three steps to get the smooth and coherent results. First of all, we used the different color spaces to reduce noise, in order to solve the shadow issue. Secondly, we choose the DMD method to extract the sparse edges. Thirdly, we used a sparse feature enhancement filter to enhance the sparse features in art images. Fig. 2 shows that the input is an art image. Then, we reduce the noises by using color space. We map the original image to HSV color space and get the luminance channel images. This is because the HSV space can detect the light better than RGB space, which will help to reduce noises in edge detection. The details will be introduced in Section 4. After that, we preprocess the luminance channel images and synthesize a video stream $\mathbf{X}$. A video stream ($\mathbf{X}_1$ to $\mathbf{X}_N$) is a uniform sampling data with N frames, and the time interval is Δt. And then, we use the DMD method to decompose reshaped video matrix into low rank matrix and sparse matrix. In order to get a better edge, we enhance the sparse feature by EDGO and map single luminance channel image to x_i $(1 \leq i \leq N)$. The $\mathbf{X}_i^{Sparse-edge}$ is the sparse edge result. Finally, we synthesize the intermediate results in eight-direction and then get the final result using noise elimination and binaryzation.

Here, the video is synthesized by N images, including N-8 copies of the original images and 8 images obtained from our gradient operator (EDGO). This is because the DMD algorithm can successfully detect sparse features (edges) enhanced by our EDGO method. In order to make a distinction with “the real video”, we call the video synthesized in the paper as “A Sequential Images Set” in the rest of this paper.

4. Color Space Based Denoise Algorithm

In this session, we will introduce noise and shadow reduction methods using different color spaces. Generally, the traditional edge detection algorithms convert the color image into a grayscale as:

$$\text{Gray} = \text{R} \times 0.299 + \text{G} \times 0.587 + \text{B} \times 0.114 \tag{1}$$

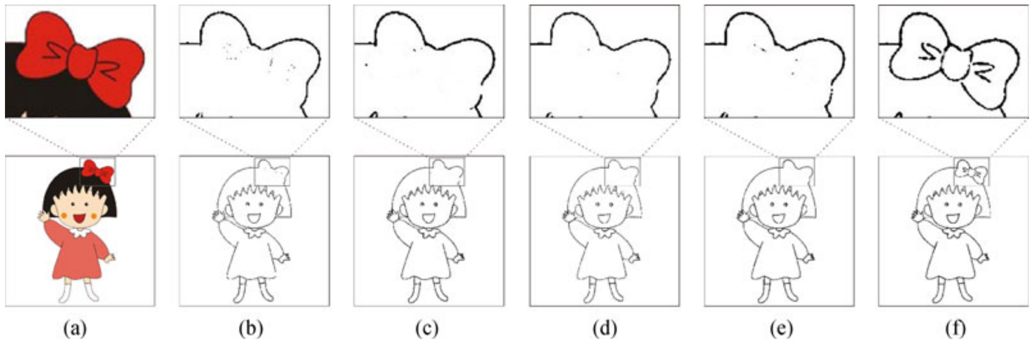

Fig. 3. Comics in different color space for DMD decomposition extract the sparse edges. (a) is the original image. (b) shows the results denoise by RGB color space. (c) shows the results denoise by LAB color space. (d) shows the results denoise by YUV color space. (e) shows the results denoise by HSI color space. (f) shows the results denoise by HSV color space. Here, the picture is from "Chi-bi Maruko".

However, the three components of RGB (red channel, green channel and blue channel) has a strong correlation, for example, when the light changes, the three components of RGB will change together. The strong correlation among the three channels is very obvious in the cartoon image. Although comics have a lot of shadows, light and shade, which make cartoon characters more vivid, the shadows, light and shade are not edges in the process of copying the cartoon images. On the contrary, some lines are not clear in the RGB color space, so they are not easy to be extracted. For example, Fig. 3(a) shows that there is a black line in the bow of the cartoon character in the original image. The black line is the boundary that needs to be extracted. Nevertheless, when we use the RGB color space, the distance between two color points is not equal to the difference of the two colors, so we cannot estimate the hue, saturation and lightness and other perceived attributes. Therefore, Fig. 3(b) shows that some edges are missing. Compared to RGB color space, HSV colors are closer to human vision. It is dedicated to perceptual uniformity, and its **V** component closely matches human brightness perception. It can be seen that different color space has a great influence on the result of edge detection.

5. Sparse Feature Enhancement

Traditional operators, such as the Sobel Operator, generally use a 3×3 kernel which is convolved with the original image to calculate approximations of the derivatives of brightness one for horizontal changes, and one for vertical. Similarly, when using the DMD (Dynamic Mode Decomposition) algorithm to extract sparse edges, the original data is required to be convoluted with the corresponding templates to obtain a new image. Inspired by other edge detection operators, we propose an 8-direction template to detect the edges of the eight-direction, as shown in Fig. 4.

Using the above template, we calculate the image at time t_{filter} $(1 < t_{filter} < m)$ using the formula (2) and increase the edge features.

$$Image_{direction} = Direction \times Image \tag{2}$$

The subscript direction means eight-direction in the template. After reconstructing the image by formula (2), we obtain different sparse lines of eight-direction, which reflect the different image features of eight-direction. Fig. 4 shows the different features between the gradient operators of eight directions. We can see that edges are extremely different between "Direction 1" and "Direction 3" in Fig. 5. This is because watercolor paintings have more types of lines including thick lines and fine lines. Using the edge operator in one direction will seriously affect the result of edge detection. For example, "Direction 6" in Fig. 5 shows that the edges of the upper left corner and the lower right corner directions are not extracted completely. Due to the different style of painters, some artists

$$\underset{\text{Direction1}}{\begin{bmatrix}1&0&0\\0&0&0\\0&0&0\end{bmatrix}}\quad\underset{\text{Direction2}}{\begin{bmatrix}0&1&0\\0&0&0\\0&0&0\end{bmatrix}}\quad\underset{\text{Direction3}}{\begin{bmatrix}0&0&1\\0&0&0\\0&0&0\end{bmatrix}}$$

$$\underset{\text{Direction4}}{\begin{bmatrix}0&0&0\\1&0&0\\0&0&0\end{bmatrix}}\qquad\qquad\underset{\text{Direction5}}{\begin{bmatrix}0&0&0\\0&0&1\\0&0&0\end{bmatrix}}$$

$$\underset{\text{Direction6}}{\begin{bmatrix}0&0&0\\0&0&0\\1&0&0\end{bmatrix}}\quad\underset{\text{Direction7}}{\begin{bmatrix}0&0&0\\0&0&0\\0&1&0\end{bmatrix}}\quad\underset{\text{Direction8}}{\begin{bmatrix}0&0&0\\0&0&0\\0&0&1\end{bmatrix}}$$

Fig. 4. Eight-direction gradient operator.

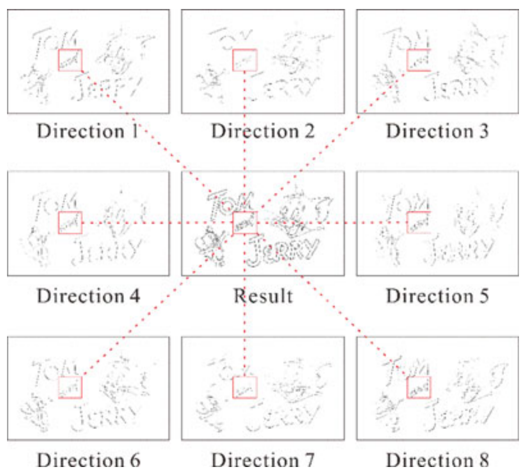

Fig. 5. The results are obtained by the gradient operator in the upper left, lower left, upper right and lower right directions. The middle result represents the synthesis of the four directions.

like to use the oblique lines to express lively and sweetly. On the other hand, other artists prefer to draw more straight lines, which creates a serious and solemn atmosphere. “Direction i” ($i = 1, 2, \ldots, 8$) of Fig. 5 detects the edge that is only in one direction of the maximum gradient amplitude. After the synthesis, you can get the most complete edges, as shown in “Result” of Fig. 5. Here, the picture is from “Tom and Jerry”.

6. Dynamic Mode Decomposition Based Edge Detection

The most important difference between art images and natural images is that art images have the very strong sparse characteristics. Almost all the art images are traced by the artists. This artificial process is actually a process of enhancing the sparse characteristics of images. There are some ways to separate low rank and sparse like Robust Principal Component Analysis (RPCA). However, the method we used is Dynamic Mode Decomposition (DMD). The advantage of DMD is faster and does not need to adjust the parameters.

The DMD (dynamic mode decomposition) is a mathematical method, which is a data-driven matrix decomposition. It can provide accurate reconstructions of spatio-temporal coherent structures arising in nonlinear dynamical systems. DMD was originally used in the field of fluid mechanics. So DMD method can be used to understand, control and simulate complex nonlinear systems. The ability of the DMD is to discover and utilize the low dimensional structure and sparse structure of complex systems. This ability is the key to solving the edge detection.

DMD algorithm is based on the premise that a given data set must be a fixed at intervals of the data. In Section 3, we define a sequential images set $\mathbf{X}_1$ to $\mathbf{X}_N$, which is a uniform sampling data with N frames, and the time interval isΔt. Time series data matrixes can be represented as

$$\mathbf{X}_1^N = [x_1\ x_2\ x_3\ \cdots\ x_N] \tag{3}$$

x_i $(1 \leq i \ \leq N)$ is an image that we map by the gradient operators of eight directions. We assume that there is a linear mapping in the process, so that we can use the Koopman operator $\mathbf{A}$ to map the data at the jth time to the data at the j + 1th.

$$x_{i\,+\,1} = \mathbf{A}x_i \tag{4}$$

We can export the following formula

$$\mathbf{AX}_1^{N-1} = \mathbf{X}_2^N \tag{5}$$

Since $\mathbf{X}_1^{N-1} = \mathbf{U}\sum \mathbf{V}^* \boldsymbol{S}$, so we can rewrite (4) in the following formation

$$\mathbf{X}_2^N \approx \mathbf{U}\Sigma\mathbf{V}^* \boldsymbol{S} \tag{6}$$

in which $\mathbf{U}$ is unitary ($\mathbf{U} \in C^{m\times l}$), Σ is diagonal ($\Sigma \in C^{l\times l}$) and $\mathbf{V}$ is unitary ($\mathbf{V} \in C^{n-1\times l}$). Parameter l is chosen to minimize x rank. We can get the following matrix $\mathbf{S}$, which is determined from the matrices of $\mathbf{X}_1^{N-1}$ and $\mathbf{X}_2^N$ by minimizing the Frobenius norm of the difference between $\mathbf{AX}_1^{N-1}$ and $\mathbf{X}_2^N$. We can get the following matrix $\mathbf{S}$

$$\mathbf{S} \approx \mathbf{V\Sigma}^{-1}\mathbf{U}^*\mathbf{X}_2^N \tag{7}$$

We can use the similarity transformation ($\mathbf{V\Sigma}^{-1}$) to derive the matrix, which is similar to the matrix $\mathbf{S}$, and denote as $\tilde{\mathbf{S}}$.

$$\tilde{\mathbf{S}} \approx \mathbf{U}^*\mathbf{X}_2^N\mathbf{V\Sigma}^{-1} \tag{8}$$

The basic idea of DMD algorithm is

$$\mathbf{AX}_1^{N-1} = \mathbf{X}_2^N \approx \mathbf{X}_1^{N-1}\mathbf{S} \tag{9}$$

We can get the DMD mode φ:

$$\varphi_j = \mathbf{U}\boldsymbol{y}_j \tag{10}$$

In addition, we can transform the eigenvalue to Fourier mode to predict time dynamic:

$$\omega_j = \frac{\ln(\mu_j)}{\Delta t} \tag{11}$$

The real part of ω_j corresponds to the growth or attenuation of the DMD basis function, and the imaginary part of ω_j corresponds to the oscillation of the DMD mode. Through $\mathbf{X}_{DMD}(t) = \mathbf{A}^t x_1$, we can reconstruct the sequential images set by

$$\mathbf{X}_{DMD}\,(t) = \sum_{j=1}^{r} \alpha_j\varphi_j\mu_j^{t-1} = \sum_{j=1}^{r} \alpha_j\varphi_j e^{\omega_j t} \tag{12}$$

It is obvious that there will be a corresponding Fourier mode (ω_j) in the complex space. According to whether ω_j is nearby 0 or not, the Fourier modes can be divided into two groups: a low rank mode and a set of sparse modes. Here, we call the low rank mode as p point, $||\omega_{j=p}|| \approx 0$. On the

Fig. 6. Test images in different characteristics, such as a single comic character, multiple comic characters, landscape painting, wall painting and oil painting. Here, the pictures from "Dunhuang Academy China" (top-right), "One Piece" (middle-left), "The Wind Rises" (middle-right), and "http://www.sccnn.com/gaojingtuku/wenhuayishu/huihuayishu/20140428-111484.html", (bottom-right), respectively.

other hand, the sum of the rest modes in the second group is the sparse part, which can be used to exact the sparse boundaries using DMD method as:

$$\mathbf{X}_{DMD}^{Sparse-mode} = \sum_{j \neq p}^{r} \alpha_j \varphi_j e^{\omega_j t} \tag{13}$$

7. Experiments

In this section, we will discuss the detailed implementation and report the algorithm performance.

Data Set: In order to evaluate the differences of results and performances among the various algorithms, our data set involves images of different resolution, sizes and styles. Referring to the different styles, we focus on comic, watercolor and printmaking. In Fig. 6, the test art images have different characteristics, such as a single comic character, multiple comic characters, animal comic, landscape painting, wall painting and oil paintings and so on. For these different kinds of paintings, our algorithm can achieve high quality results from Fig. 10. The sparse edges of each result are clean, smooth and coherent, with little noise. Here, we will analyze the three kinds of art images one by one.

7.1 Edge Detection in Comic

There are many types of comics. However, the common feature of these comics is that cartoonists draw sketches, firstly. Secondly, the artist colored sketches to get the final color comics. Sketch has a strong sparseness; the color of the process does not affect its sparse features. The DMD algorithm can be used for edge detection in comic. We compared with the common edge detection algorithms including Sobel operators, Canny edge detection and Roberts operators. Fig. 7 shows that our algorithm is more coherent than the Sobel operators, Canny edge detection and Roberts operators. Although Canny edge detection can detect more edges, the results have some false edges and some ambiguous edges of Fig. 7. The false edges are represented by clouds, but in the image clouds are not the main body of comic. The eyes of the characters of the comic appeared ambiguous edges. The reason for these edges is that the line near the eyes is not a thin strip. Canny edge detection, Sobel operators and Roberts operator's algorithms will detect two edges

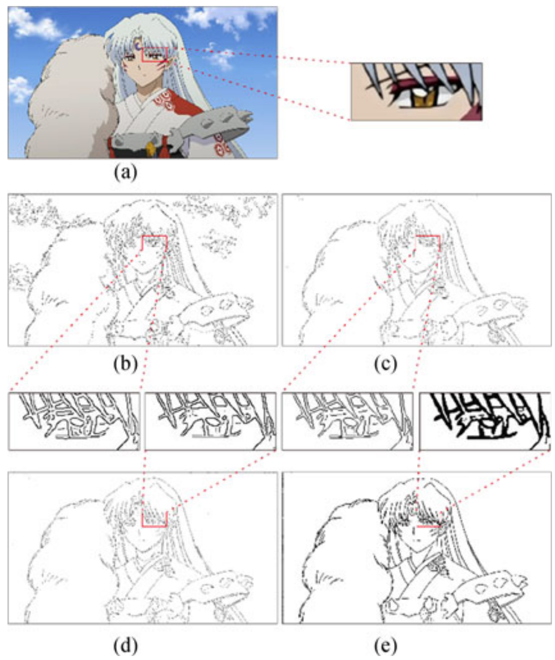

Fig. 7. Our algorithm is compared with other algorithms in comic. (a) is the original image. (b) shows the results detect by Canny edge detection. (c) shows the results detect by Roberts operators. (d) shows the results detect by Roberts operators. (e) shows the results detect by our method.

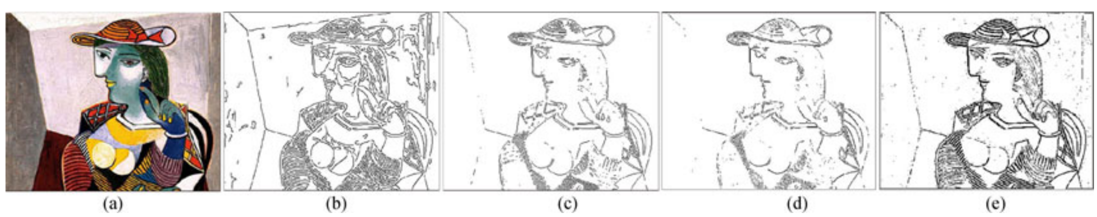

Fig. 8. Our algorithm is compared with other algorithms in oil painting. (a) is the original image. (b) shows the results detect by Canny edge detection. (c) shows the results detect by Roberts operators. (d) shows the results detect by Roberts operators. (e) shows the results detect by our method.

when the line is thick. The results of our algorithm get a thick edge in Fig. 7. Our algorithm is more aesthetic feeling than other algorithms.

7.2 Edge Detection in Watercolor Painting

Shadow and shading in the comics are to make objects more stereoscopic. The shadow of the transition is not an edge, because the excessive area is caused by color contrasts visual difference, not the real painting boundaries. In the result, the shadow boundary should be detected as little as possible. Fig. 7 shows that due to the large number of characters of the comic, other edge detection methods get messy results. Therefore, these results cannot be used as comic copies or study painting skills. In contrast, our results are less noisy, more smooth and vivid.

Similar to comics, watercolor painting has sparse feature either. Similarly, we do experiment with a Picasso's paintings to test the differences between common algorithms and ours in Fig. 8. The results of the edge detection based on common algorithms have lost the aesthetic of the original image. Our algorithm preserves a lot of useful edges information details. From the results, we find that our approach is superior to the others in some way.

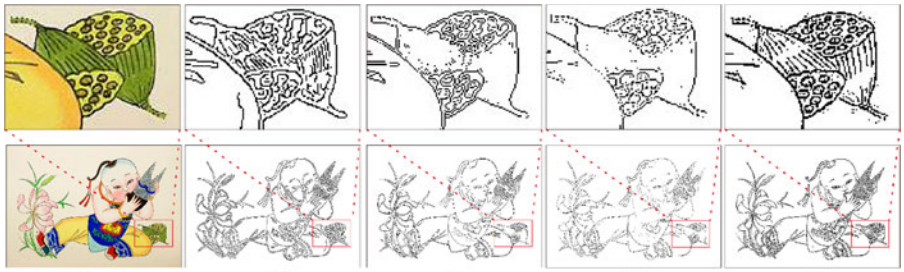

Fig. 9. Our algorithm is compared with other algorithms in printmaking. (a) is the original image. (b) shows the results detect by Canny edge detection. (c) shows the results detect by Roberts operators. (d) shows the results detect by Roberts operators. (e) shows the results detect by our method.

Fig. 10. The results in different art images.

7.3 Edge Detection in Printmaking

Watercolor painting is different from comics because it has more lines. This problem leads to Canny edge detection and Sobel operators results with double lines. Fig. 8 shows the results of the wall painting in different algorithms. The results of Canny edge detection and Sobel operators have a lot of double lines and cannot be copied.

The results of the edge detection from the eight-direction template are shown in Fig. 9. The sparse edges extracted from each direction are incomplete and are only part of the sparse features in that direction. Then we propose to synthesize the results of eight-direction or just four orthogonal directions or four diagonal directions, and the three kinds of synthetic results. From the figure, we can conclude that there is less noise in the sparse edge detecting results synthesized by four diagonal directions, while there are more abundant lines of the sparse edge detection results synthesized by eight-direction.

A printmaking is printed in a printed or etched plate, so printmaking also has strong sparse feature. There are many kinds of printmaking, especially in China. It is very difficult to detect the edges, because most printmakings have high resolution and dense color. From Fig. 9, it can be seen that the result of printmakings is much worse than the comics and oil paintings. Our algorithm is still better than other algorithms. It is obvious that our result has less noise, clearer and smoother edges. Fig. 10 shows the results in different art images.

8. Conclusion and Future Work

In this paper, we have proposed an edge detection algorithm based on dynamic mode decomposition, which is used to detect edges of art images. In our method, we first convert the original color image into the single channel image. After the neighborhood convolution, we use the dynamic mode decomposition to extract the sparse edge components. Compared with the traditional edge detection algorithms, our method is more excellent and the algorithm is easy to be implemented, with less noise, clearer and more coherent edges. Furthermore, our method has successfully resolved the problems of False Edge, Shadow, and Double Line, which cannot be well dealt with by existing methods. For example, the shadow of art images would be detected as edges by Sobel algorithm. The thick lines are judged as double lines by existing algorithms, such as Canny, Sobel Roberts, and Laplacian methods, and so forth.

Our method mainly deals with images of high sparseness. The edge detecting problems of images with low sparseness are not ideal, such as ink painting and natural images like landscape and character photos. This will be our first future work, to study more about the sparseness extraction process of DMD algorithm. We will try to improve it to obtain the low sparseness properties, so that we can extend our work to detect the edges of nature images. In addition, eight-directions gradient operator will cause some noise and reduce the quality of the results for low contrast image. In order to resolve this problem, our future work will try to propose an improved operator, which can fully support the sparseness extraction process of DMD algorithm. Besides, this work can give a reference to many research fields [50]–[59], such as intelligent vehicle, intelligent transportation system and internet of things. In all, we will improve our method and apply it to natural and low contrast images.

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